# Digital Shadow Framework for Construction Progress Monitoring

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**Abstract**
As Building Information Modelling (BIM) and Construction 4.0 gain traction, tracking project progress in real time has become increasingly critical. Although Digital Twins offer advanced capabilities, their reliance on complex, bidirectional data exchange often hinders practical deployment during active construction. To overcome this limitation, this study introduces a BIM-enabled Digital Shadow (DS) framework. By utilizing a streamlined, unidirectional data flow from the physical job site to its digital counterpart, the proposed framework integrates BIM, the Internet of Things (IoT), computer vision, cloud computing, and artificial intelligence (AI) for efficient progress monitoring. The architecture comprises six sequential layers: Physical Construction, Data Acquisition, Digital Integration, Analytics, Visualization, and Decision Support. To validate this model, a two-round Delphi study was conducted with 30 multidisciplinary experts specializing in BIM, construction management, AI, IoT, computer vision, cloud computing, and Construction 4.0. The evaluation revealed strong consensus across all framework components, yielding median scores of 4–5, interquartile ranges of 0–1, and agreement levels between 80% and 100%, thereby fulfilling all predefined validation criteria. These findings establish both the conceptual soundness and practical viability of the proposed framework. This research advances digital construction by offering a workable DS architecture that synthesizes heterogeneous site data to support automated progress tracking, live visualization, and informed decision-making, ultimately laying a solid foundation for future prototype development and real-world smart construction deployment.

**Keywords:** Building Information Modelling (BIM), Digital Shadow, Construction 4.0, Real-Time Progress Monitoring, Internet of Things (IoT), Computer Vision, Delphi Study.

## Introduction

Construction 4.0 merges tools like BIM, IoT, AI, computer vision, cloud computing, robotics, and cyber-physical systems to drive data-centric project management. These innovations boost automation, teamwork, efficiency, and choices across today's builds. Smart Construction taps into these assets using sensing, messaging, and analytics to track and steer projects on the fly. Gear like drones, RFID chips, GPS tags, body-worn sensors, and machine learning models make it possible to automatically follow progress, output levels, safety stats, and material use. At the center of it all sits BIM, serving as the main hub that binds together shapes, budgets, and timelines into one cohesive blueprint. Even so, standard BIM falls short because it relies on manual tweaks and struggles to capture the shifting reality of a busy job site. By bringing in IoT, AI, and computer vision, BIM gets a serious upgrade, allowing for live data gathering and automated checks on site work. Even with all these tech leaps, today's setups tend to stay siloed, tackling narrow tasks instead of working together as a whole. While Digital Twins bring heavy firepower, they often prove too heavy-handed for field use due to strict two-way data demands and high overhead. Digital Shadows present a cleaner, more practical alternative through simple one-way syncing, underscoring why the industry urgently needs unified frameworks to power non-stop site tracking and smarter choices

## 2. Literature review

### 2.1 Construction 4.0: Evolution of Digital Transformation in Construction

Early efforts in construction automation largely relied on isolated tools, such as tracking project progress by matching photogrammetry-based point clouds with 4D BIM models. Over time, refined alignment and analysis methods significantly boosted the accuracy and dependability of these progress-tracking techniques [1]. Later research shifted toward merging IoT and big data with BIM, giving rise to BIM 4.0—a dynamic platform built for continuous project oversight and information management. These studies stressed that Construction 4.0 derives its true value from seamless interoperability, smart information sharing, and unified decision-making rather than fragmented software solutions [2]. Complementing these insights, bibliometric reviews regularly pinpoint BIM, IoT, robotics, big data analytics, virtual reality, and additive manufacturing as the core technological pillars powering digital transformation across the construction sector [3].

### 2.2 Smart Construction: Towards Intelligent Project Management

Smart Construction brings the core ideas of Construction 4.0 to life by blending sensors, automation, AI, and digital networks to keep tabs on projects non-stop and boost overall performance. It swaps out old-school periodic check-ins for live data feeds coming straight from IoT gear, drones, RFID trackers, GPS tags, body-worn wearables, laser

scanners, and computer vision setups. Meanwhile, AI and machine learning step in to forecast issues, spot safety hazards, streamline resource use, and automatically track project milestones. Even though tools like BIM, IoT, AI, cloud networks, drones, robotics, computer vision, and Digital Twins are widely used, current deployments remain siloed and locked into narrow, single-use tasks. Because of this, the industry desperately needs unified digital architectures that bridge the gaps, allowing for seamless interoperability, continuous tracking, smart analytics, and better-informed choices from start to finish.

**2.3 Construction 4.0 and Smart Construction for Progress Monitoring**

Recent literature splits digital representations into three clear tiers based on how the physical and digital worlds interact: Digital Models (DMs), Digital Shadows (DSs), and Digital Twins (DTs). While a DM remains static and a DS relies on a straightforward, one-way data flow, a DT demands complex, two-way communication. Even so, the sheer difficulty of setting up a true DT means most real-world projects never advance past the DM or DS stages [23]. Across the architecture, engineering, and construction (AEC) sector, DTs are increasingly used for tracking projects, managing assets, and handling predictive maintenance, but widespread adoption is still choked off by steep costs, technical hurdles, skill shortages, and cybersecurity worries. Pushing past these barriers requires better software compatibility, stronger team training, and tighter security protocols [24]. At the same time, merging BIM with IoT and big data has pushed traditional modeling toward BIM 4.0, building a much sturdier foundation for digital tracking. Rather than sitting as a static digital filing cabinet, BIM has evolved into a live platform capable of absorbing job site data on the fly. This transition unlocks smoother workflows, constant data sharing, and better-coordinated project management across the entire construction lifecycle [2].

**2.4 Building Information Modelling (BIM) for Construction Progress Monitoring**

The widespread use of BIM has heavily accelerated digital growth and tech innovation across the construction sector. Fresh breakthroughs in information technology have cleared the path for AI-powered solutions like automated blueprint design, regulatory code checks, and construction robotics. Even so, plenty of research hurdles still stand in the way of rolling out the next wave of smart building systems [25]. Today, BIM serves as an essential pillar of Construction 4.0, weaving together physical shapes, property data, timelines, and budgets into a single cohesive model that supercharges teamwork, visuals, and choices from day one to project closeout. Building on this, the arrival of 4D BIM has completely transformed how teams track project pace by tying schedules directly to 3D designs, making it much easier to hold planned timelines up against actual site progress.

**2.5 Internet of Things (IoT) in Construction Monitoring**

Bibliometric research consistently highlights IoT, BIM, AI, robotics, big data analytics, virtual reality, and additive manufacturing as the main drivers of digital evolution in the construction space [3]. At the same time, systematic reviews point to a rapid convergence of AI, IoT, BIM, Digital Twins, and computer vision across the industry. This synergy is fueling interconnected ecosystems that boost automation, streamline risk handling, and drive data-backed choices from project launch to completion [27]. While old-school progress tracking has traditionally relied on manual walkthroughs and sluggish paperwork—leading to delayed and subjective updates—the Internet of Things unlocks non-stop, automated data gathering via sensors, RFID tags, GPS trackers, UWB nodes, drones, body-worn gear, and smart cameras. When IoT merges with BIM, static 3D models transform into living frameworks capable of tracking job site progress on the fly, keeping an eye on resources, and catching schedule slips early. Layering in cloud computing, edge networks, and AI takes these capabilities even further, offering scalable data handling, predictive analytics, and smart decision support.

**2.6 Artificial Intelligence and Computer Vision for Construction Progress Monitoring**

AI has quickly become a cornerstone of Construction 4.0, driving the automated analysis of massive, varied job site data to power smarter choices. It covers a broad spectrum of techniques, including machine learning, deep learning, natural language processing, neural networks, and computer vision. Computer vision plays an especially vital role by automatically processing visual data and 3D scans captured by cameras, drones, and laser scanners to keep a precise eye on construction progress. Together, AI and computer vision are reshaping project management, swapping out slow, manual reporting for sharp, automated, data-centric oversight [27]. Digging into a systematic review of 80 industry studies reveals that deep learning is heavily relied upon across the sector for tracking machinery, catching construction defects, inspecting infrastructure, managing workflows, and breaking down point clouds. These practical uses dramatically boost automation, sharpen object recognition, and improve day-to-day operational monitoring on modern builds [31].

**2.7 Cloud-Based Construction Management**

Merging cloud computing with Building Information Modelling has given rise to Cloud-BIM, which drives centralized, team-wide coordination and synchronized project record management. Although Cloud-BIM sees heavy use during planning, design, and active building phases, its footprint in facility management, maintenance, and operations is still relatively small. This gap is largely driven by roadblocks like cybersecurity worries, software compatibility issues, questions over data ownership, and legal complications [30]. At the same time, cloud

infrastructure supplies the heavy computational muscle required for Digital Twins, linking up sensing gear, analytics, simulations, and scalable data storage. Even so, pulling off a successful Digital Twin still demands solid semantic structures, compatible data pipelines, standard protocols for information exchange, and efficient handling of continuous data feeds [29]. Cloud computing pulls IoT hardware, BIM models, AI engines, computer vision tools, and project management apps into one centralized hub designed for live site progress tracking and collaborative choices. It keeps physical job site data constantly synced with BIM layouts, powering automated progress checks, predictive insights, and executive dashboards. Because of this, the industry needs cloud-driven Digital Shadow setups to deliver scalable, compatible, and continuously refreshed tracking for modern construction.

**2.8 Construction Safety Monitoring**

Recent breakthroughs in AI, computer vision, BIM, IoT, RFID, wearable sensors, and cloud computing have shifted job site safety from reactive walkthroughs to proactive risk prevention. These innovations drive automated hazard spotting, safety training, monitoring, and risk reduction. Even so, adoption remains spotty—especially in developing regions—held back by economic, organizational, and tech hurdles [34]. Computer vision, particularly deep learning models like YOLO, has proven invaluable for automated hazard detection by constantly scanning for workers, machinery, missing PPE, and dangerous conditions. AI-driven PPE checks sharpen compliance and cut down on slow manual oversight through precise, live monitoring [32]. The tangible impact of smart safety gear is also backed by empirical studies. Research using the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF) framework shows that strong automation, interoperability, information sharing, and sustainability significantly boost safety performance. These factors raise how useful and user-friendly teams perceive these tools to be, driving a higher willingness to adopt digital safety management platforms [35]. On the hardware side, IoT upgrades safety by keeping a constant eye on crews, equipment, and environmental factors using RFID tags, body-worn gear, position trackers, and physical sensors. These setups speed up emergency responses and catch hazards early, though steep setup costs and technical skill gaps still slow down mass adoption [36]. Despite rapid tech leaps, a wide chasm remains between academic research and everyday job site execution, with many practitioners still leaning on old-school safety methods. While studies increasingly focus on AI, computer vision, simulations, and intelligent hazard alerts, these tools have yet to become standard practice across the wider construction sector [33].

**2.9 Equipment Monitoring**

Recent advances in Construction 4.0 have paved the way for smart monitoring by blending Digital Twins, artificial intelligence, computer vision, cloud infrastructure, and reality-capture tools, giving teams live insights into project pace, output rates, and safety records. Digital Twins have stepped up as a promising cyber-physical method, tying diverse data feeds directly to active digital models of construction workflows. Recent studies prove their worth in tracking equipment output and guiding day-to-day decisions using automated data collection paired with cloud-hosted dashboards [37]. On the capture side, tools like mobile laser scanning, LiDAR, and point-cloud pipelines allow for the rapid creation of high-precision 3D site models. When paired with automated scanning, mesh generation, and point-cloud alignment, these systems back up site reconstruction, structural recognition, and automated earthwork tasks, building a sturdy digital base for smart site monitoring [40]. At the same time, computer vision has turned into a core pillar for tracking construction resources automatically. Advanced deep learning setups, like YOLO, accurately spot and follow workers, machinery, and materials even under rough job site conditions involving blind spots or changing light. Recent research highlights how well these models sharpen resource control, daily efficiency, and crew safety [41]. Smart sensing and spatial checks using point clouds have also upgraded safety protocols, allowing for round-the-clock tracking of heavy gear, collision risk estimates, and automated warnings during heavy lifts. These techniques make clash detection sharper and foster safer planning by mapping out how cranes and nearby structures interact over time and space [38, 39].

**2.10 Material Tracking**

Keeping materials, equipment, and crews properly managed is vital for hitting schedule targets and keeping output high, yet old-school tracking often leaves teams dealing with delayed updates and poor coordination. Construction 4.0 tackles these hurdles head-on through automated data gathering, continuous tracking, and connected information sharing across every phase of a project. Recent studies show that blending the Internet of Things, local sensors, position tracking, and machine learning sharpens logistics, resource monitoring, and day-to-day efficiency. When paired with linked data models and key performance indicators, these setups boost production visibility, clear the path for just-in-time material drops, and streamline how resources are deployed [42]. On the supply chain side, IoT has transformed material oversight by enabling live tracking, instant updates, and tight inventory control. Tying IoT directly into enterprise resource planning (ERP) software further strengthens production coordination, supports lean inventory practices, and drives overall efficiency through automated data entry [44]. At the same time, leaps in positioning gear, barcode scanners, GPS tags, and mobile sensors have unlocked automated tracking and documentation for building materials, boosting logistical flow. Smartphone sensors paired with machine learning also offer a budget-friendly way to recognize

equipment activity, measure output, and run operational checks [43]. Even though great strides have been made in tracking materials, monitoring machinery, managing logistics, and streamlining workflows, most current solutions remain siloed and locked into narrow, single-purpose applications. A Digital Shadow framework directly solves these fragmentation issues by pooling data from IoT hardware, GPS trackers, mobile sensors, ERP platforms, barcode readers, and BIM layouts into a single, unified environment via one-way information syncing. This integrated approach powers clear resource visualization, deeper productivity analysis, smarter choices, and vastly improved construction progress monitoring.

**2.11 Workforce Monitoring**

Computer vision has firmly established itself as a primary tool for tracking and assessing construction crews, driving worker detection, movement tracking, activity recognition, and safety oversight through advanced object detection models. Despite major strides, hurdles related to software stability, scalability, and chaotic job site environments still linger, though emerging generative AI tools point toward exciting new ways to bridge those gaps [47]. Deep learning has significantly elevated how teams evaluate workforce performance by automatically breaking down video feeds to measure output objectively. These AI-powered activity trackers sharpen performance metrics, highlight productivity gaps, and guide targeted training while cutting out the need for tedious manual check-ins [46, 49].

Bridging BIM with computer vision further supercharges crew safety, fusing rich spatial and semantic building data with live visual streams to pinpoint worker locations and spot hazards with high precision. This integration powers timely safety alerts and proactive accident prevention [48]. Meanwhile, body-worn wearables track workers' physiological signs, daily behaviors, and occupational health in real time, keeping productivity and safety checks finely tuned. Recent literature underscores why combining multiple data streams, advanced analytics, and optimized sensors is essential for building truly smart workforce monitoring networks [50].

**2.12 Digital Shadow and Digital Twin in Construction**

The swift rise of Construction 4.0 has evolved traditional BIM into smart cyber-physical networks by weaving together BIM, IoT, artificial intelligence, computer vision, cloud infrastructure, and advanced data analytics to back automated tracking, predictive insights, and informed decisions from project kickoff to closeout. Over time, digital models have journeyed from static DMs to rich BIM formats, and onward to continuously updated digital spaces powered by modern sensing and communication tools. Looking at how closely the physical and digital worlds interact, digital maturity breaks down into three tiers: Digital Models (DMs), Digital Shadows (DSs), and Digital Twins (DTs), which stand for static, one-way synchronized, and fully two-way systems, respectively. Out of these options, the Digital Shadow stands out as a practical, middle-ground choice, keeping digital records freshly updated with live field data while sidestepping the steep technical hurdles of a fully bidirectional Digital Twin setup.

As an attractive alternative to full Digital Twins, the Digital Shadow has captured growing interest by offering continuous, one-way data syncing from job sites to digital models without the headache of complex two-way control loops. By blending BIM, IoT, AI, computer vision, cloud platforms, and advanced analytics, a Digital Shadow delivers live visibility into project progress, crew workflows, machinery performance, material logistics, and site conditions, driving effective oversight and smarter choices. Even though Digital Twins offer advanced perks like deep simulations, automated optimization, predictive maintenance, and closed-loop feedback, rolling them out in practice is still bogged down by software compatibility issues, heavy computing demands, and organizational roadblocks. Because of this, current research increasingly views the Digital Shadow as a much more viable path for tracking construction progress. However, comprehensive Digital Shadow frameworks that pull together multiple Construction 4.0 technologies are still hard to come by and are rarely put through rigorous expert validation. To fill this blank space, this study introduces and validates an integrated Digital Shadow framework using the Delphi method, proving its thoroughness, operational utility, and real-world feasibility for non-stop construction progress tracking.

**3. Research Gap**

Existing literature shows that Construction 4.0 innovations—such as BIM, IoT, AI, computer vision, Digital Shadows, and Digital Twins—have heavily upgraded project progress tracking through better visuals, automated data collection, predictive modeling, and digital teamwork. Even so, current research remains scattered. Most of these tools are still studied on their own or through narrow, two-way pairings. Traditional BIM platforms still lean heavily on manual tweaks, IoT rollouts tend to be siloed and lack software compatibility, and AI or computer vision models are usually built as standalone utilities rather than plugging into a full-scale monitoring network. On top of that, Digital Shadows have flown somewhat under the radar compared to Digital Twins, leaving a clear void: no standardized or tested framework currently exists to bind BIM, IoT, AI, and computer vision together into a unified Digital Shadow architecture for round-the-clock site tracking.

**Building on these insights, the literature review highlights five core research gaps:**

- Research Gap 1: Existing BIM-based tracking systems remain static information hubs, lacking a true Digital Shadow framework to keep real-time job site data continuously synced with the BIM

model.

- Research Gap 2: Current IoT monitoring setups are heavily fragmented, failing to provide an integrated Digital Shadow architecture that can pull diverse sensor data into a living, constantly updated digital replica.
- Research Gap 3: AI and computer vision applications usually operate as isolated analytical tools, missing vital integration with BIM and IoT within a cohesive Digital Shadow framework for automated progress checks and smart choices.
- Research Gap 4: The construction sector lacks a validated Digital Shadow framework that systematically blends BIM, IoT, AI, and computer vision into a single architecture for real-time progress tracking. While academics frequently chase after full Digital Twins, practical Digital Shadow rollouts remain largely unchartered territory.
- Research Gap 5: Very few studies have actually validated conceptual frameworks for Digital Shadow-based monitoring using structured expert consensus methods like the Delphi technique.

Together, these gaps justify building and testing a comprehensive Digital Shadow Framework for Construction Progress Monitoring. By merging BIM, IoT, AI, and computer vision into a unified architecture, this framework delivers continuous real-time data syncing, automated progress tracking, and intelligent decision support where the industry needs it most.

## 4. Research Need

To bridge these gaps, this study introduces a comprehensive Digital Shadow framework designed for real-time construction progress monitoring through the synergy of BIM, IoT, artificial intelligence, and computer vision. The proposed model weaves together live data gathering, BIM-driven digital modeling, AI-powered analytics, computer vision progress tracking, cloud storage, and decision-making tools into a single, multi-layered architecture. To ensure its reliability, the framework is rigorously evaluated using the Delphi method, testing its overall completeness, practical viability, technical feasibility, and readiness for real-world Construction 4.0 environments. Ultimately, this research contributes to the field by offering a scalable, workable Digital Shadow solution that successfully bridges the gap between old-school, static BIM workflows and overly complex, fully autonomous Digital Twin setups.

## 5. Research Objectives

To achieve the overarching goals of this research, the specific objectives of this study are outlined as follows:
a) Literature Review & Gap Identification: To critically review existing literature on BIM, IoT, artificial intelligence, computer vision, Digital Shadows, and Digital Twins for construction progress monitoring, thereby identifying key research gaps.
b) Functional Requirements Analysis: To map out the essential functional components, data sources, information flows, and system integration requirements needed to build a Digital Shadow-based progress monitoring platform.
c) Conceptual Framework Development: To build a conceptual Digital Shadow framework that blends BIM, IoT, AI, and computer vision into a cohesive architecture for continuously syncing physical job site work with its digital model.
d) System Architecture & Data Flow Design: To establish the underlying system layout, data pipelines, communication protocols, analytical engines, and decision-support tools required for automated, live construction tracking.
e) Expert Validation via Delphi Technique: To evaluate and validate the proposed Digital Shadow framework through structured expert feedback using the Delphi method, ensuring its thoroughness, practical value, technical feasibility, and effectiveness.
f) Establishing a Validated Blueprint: To deliver a fully validated Digital Shadow model that empowers Construction 4.0 projects with continuous real-time progress tracking, automated assessments, and sharper, data-driven decision-making.

## 6. Research Methodology

This research employs a qualitative framework development methodology, underpinned by a systematic literature review and rigorous Delphi expert validation. The primary aim is to conceptualize and validate an integrated Digital Shadow framework that fuses BIM, the Internet of Things, artificial intelligence, computer vision, cloud computing, and advanced data analytics to achieve real-time construction progress monitoring.

### 6.1 Systematic Literature Review:

This research utilized a qualitative framework development methodology combining a systematic literature review with a Delphi expert validation process. The primary objective was to design and validate an integrated Digital Shadow (DS) framework that fuses Building Information Modelling (BIM), the Internet of Things (IoT), artificial intelligence (AI), computer vision, cloud computing, and data analytics for real-time construction progress monitoring. The methodology is structured across six sequential phases, as illustrated in Figure 1.

**Phase 1: Systematic Literature Review**

The theoretical foundation of the framework was established through a systematic literature review. Peer-reviewed journal articles published between 2015 and 2025 were retrieved from major academic databases, including Scopus, Web of Science, ScienceDirect, IEEE Xplore, and Google Scholar. The review targeted core themes such as Construction 4.0, smart construction, BIM, IoT, AI, computer vision, Digital Shadows, Digital Twins, and construction progress monitoring. Critical analysis of these selections identified enabling technologies, system

architectures, implementation strategies, existing limitations, and critical knowledge gaps.

**Phase 2: Identification of Research Gaps**

A critical synthesis of the literature revealed four primary limitations in current progress monitoring approaches: a) A lack of integrated BIM–IoT–AI monitoring systems, b) The limited application of Digital Shadows within the construction sector, c) The fragmented implementation of AI and computer vision technologies and d) The absence of validated Digital Shadow frameworks specifically tailored for real-time construction progress monitoring.

These findings demonstrated the clear need for a comprehensive conceptual framework capable of unifying multiple Construction 4.0 technologies within a single operational environment.

**Phase 3: Development of the Digital Shadow Framework**

In response to the identified gaps, a conceptual Digital Shadow framework was developed around a six-layer architecture: a)Physical Construction Layer: Encompassing workers, equipment, materials, and site activities, b)Data Acquisition Layer: Utilizing IoT sensors, RFID, GPS, UAVs, cameras, and laser scanners, c) Digital Integration Layer: Integrating BIM, cloud databases, data synchronization protocols, and the Digital Shadow repository, d) Analytics Layer: Incorporating artificial intelligence, machine learning, computer vision, and predictive analytics, e) Visualization Layer: Featuring BIM dashboards, progress visualization, key performance indicator (KPI) tracking, and automated alert generation and f) Decision Support Layer: Supporting progress evaluation, delay prediction, resource optimization, and project control.

The architecture relies on one-way data synchronization from the physical site to its digital representation, marking the core characteristic of a Digital Shadow. The complete framework layout is detailed in Figure 2 and Figure 3.

**Phase 4: Questionnaire Development**

To validate the framework, a structured questionnaire was designed around six core evaluation dimensions: a) Framework completeness, b) Technical feasibility, c) Practical applicability, d) Data integration capability, e) Decision-support effectiveness and f) Overall usefulness.

Each evaluation item was measured using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

**Phase 5: Delphi Validation**

The framework was evaluated and refined using the Delphi technique, a recognized consensus-building method in engineering and construction research. A purposive sample of 30 experts was recruited from academia, construction firms, BIM consultancies, digital transformation practices, and project management sectors. Selection criteria required participants to possess: a) A minimum of 10 years of professional experience, b) Demonstrated expertise in BIM, IoT, AI, Digital Twin technologies, or construction management and c) A track record of relevant research publications or industry implementations.

The Delphi panel comprised 30 specialists across eight core domains: BIM specialists (5), construction and project management professionals (5), AI and machine learning experts (4), computer vision researchers (3), IoT and sensor specialists (3), cloud computing and data analytics professionals (3), Digital Twin and Digital Shadow specialists (4), and Construction 4.0/smart construction experts (3).

The validation process spanned two iterative rounds. In Round 1, experts evaluated the framework and provided qualitative feedback and recommendations for refinement. The framework was subsequently updated based on their consensus and redistributed for Round 2 evaluation. Agreement levels were quantified using descriptive and reliability statistics, including mean scores, standard deviations, percentage agreement, Kendall's coefficient of concordance (W), and Cronbach's alpha, with a consensus threshold established at 75% or higher.

**Phase 6: Final Framework Development**

Following the successful completion of the Delphi rounds, the framework was finalized to incorporate expert recommendations. The resulting architecture integrates continuous real-time data acquisition, Digital Shadow synchronization, AI-driven progress analysis, computer vision-based activity recognition, BIM-based visualization, and intelligent decision support into a cohesive system. This validated framework provides a scalable, practical foundation for deploying Digital Shadow technology in Construction 4.0 initiatives, driving automated progress tracking, responsive decision-making, and enhanced project control.

## 7. Methodological Contribution

This proposed methodology significantly advances current construction monitoring research by moving beyond isolated technological applications and establishing a cohesive pathway that blends literature synthesis, framework conceptualization, and structured expert validation. By unifying BIM, IoT, artificial intelligence, computer vision, and cloud computing within a single Digital Shadow architecture, this approach bridges the long-standing divide between academic theory and practical site execution. Furthermore, incorporating the Delphi technique ensures robust methodological rigor, validating and refining the framework through specialized expert consensus prior to deployment. This guarantees that the final architecture is reliable, highly applicable, and fully tailored to the demands of modern Construction 4.0 and smart building initiatives.

## 8. Results

Following the Delphi evaluation rounds, the collected expert responses were systematically compiled and analyzed. The resulting descriptive statistics—covering framework completeness, the individual

architectural layers (physical construction, data acquisition, digital integration, analytics, visualization, and decision support), practical implementation considerations, and overall evaluation metrics are detailed across Tables 1 through 9, respectively.

**9. Discussion**

The Delphi Round-1 results show overwhelming expert consensus on the foundational completeness of the framework, as well as its physical construction and data acquisition layers.

Framework Completeness: The Delphi Round-1 analysis demonstrated a high level of expert consensus regarding the completeness of the proposed Digital Shadow (DS) framework. All framework completeness indicators (FC1–FC5) satisfied the predefined consensus criteria, with median scores ranging from 4 to 5, interquartile ranges between 0 and 1, and agreement levels ranging from 90.0% to 100.0%. Among the evaluated indicators, FC2 achieved unanimous agreement from all 30 experts (Mean = 5.00; SD = 0.00), while FC3 also demonstrated exceptionally strong consensus (Mean = 4.80; IQR = 0.00). The remaining indicators (FC1, FC4, and FC5) attained mean scores above 4.00, reflecting broad agreement that the proposed framework comprehensively captures the essential components required for BIM-enabled Digital Shadow–based construction progress monitoring. Overall, these findings (table 9) confirm that the framework is comprehensive, conceptually sound, and sufficiently mature to proceed to the subsequent stage of Delphi validation and practical implementation.

Physical construction layer: The Delphi Round-1 evaluation of the physical construction layer demonstrated a high level of expert consensus across all five indicators (PL1–PL5). The median scores ranged from 4 to 5, while the interquartile ranges were between 0 and 1, satisfying the predefined consensus criteria. Agreement levels exceeded 96% for all indicators, with PL2 and PL4 achieving complete agreement among the expert panel. Mean scores ranged from 4.27 to 4.90, indicating strong expert endorsement of the proposed framework components. These findings (table 10) validate that the Physical Construction Layer comprehensively captures the essential elements of construction site activities required for BIM-enabled Digital Shadow-based progress monitoring and is appropriate for integration within the overall framework.

Data Acquisition Layer: The Delphi Round-1 evaluation of the Data Acquisition Layer demonstrated strong expert consensus across all five assessment items (DA1–DA5). The median scores ranged from 4 to 5, with interquartile ranges of no more than 1, satisfying the predefined consensus criteria. Agreement levels varied between 86.7% and 100%, indicating broad acceptance of the proposed framework components. DA2, DA4, and DA5 achieved complete expert agreement, while DA3 also received strong support with a mean score of 4.57. Although DA1 exhibited slightly greater response variability, it still achieved an agreement level well above the acceptance threshold. These findings (table 11) validate that the proposed Data Acquisition Layer comprehensively incorporates the essential technologies for capturing real-time construction information and is appropriate for inclusion within the BIM-enabled Digital Shadow framework.

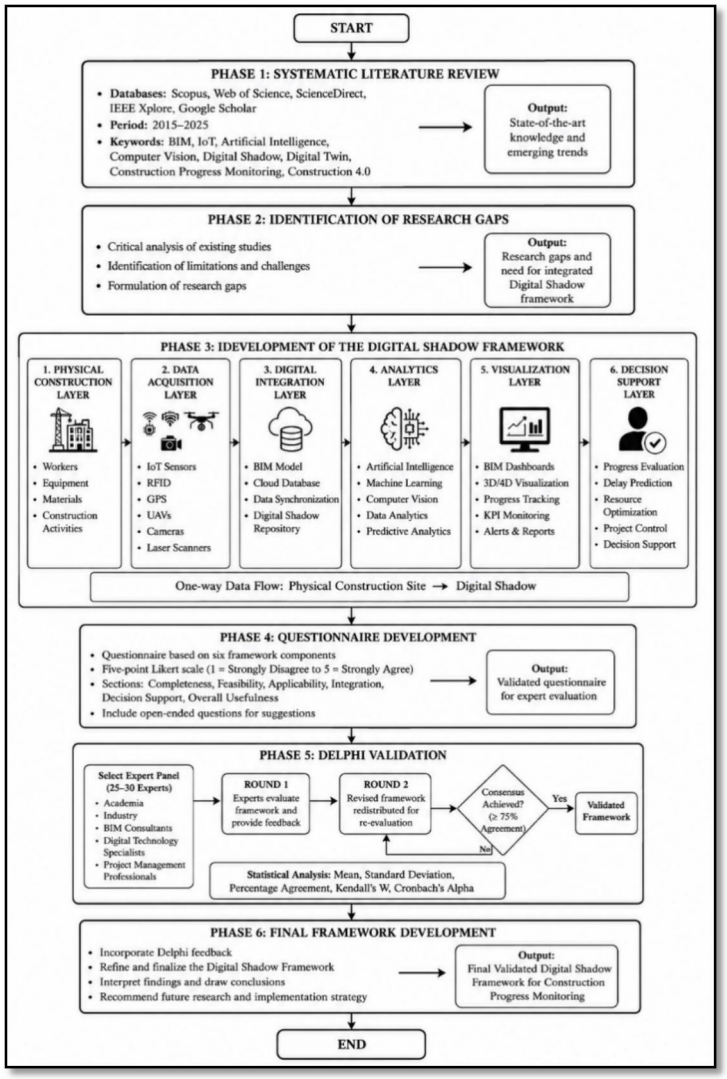


**Figure 1 Research Methodology**

Digital Integration Layer: The Delphi Round-1 assessment of the Digital Integration Layer demonstrated strong expert consensus across all five evaluation items (DI1–DI5). Median scores ranged from 4 to 5, interquartile ranges were no greater than 1, and agreement levels exceeded the predefined threshold of 75% for every indicator. Complete agreement was achieved for DI2, DI4, and DI5, while DI5 exhibited the highest response consistency (IQR = 0). Although DI1 received comparatively lower ratings, it still attained an agreement level of 83.3%, indicating broad expert acceptance. Overall, the findings (table 12) validate that the proposed Digital Integration Layer successfully incorporates the essential mechanisms required to integrate physical construction data with BIM-enabled Digital Shadow environments, supporting reliable real-time synchronization and information exchange within the proposed framework.

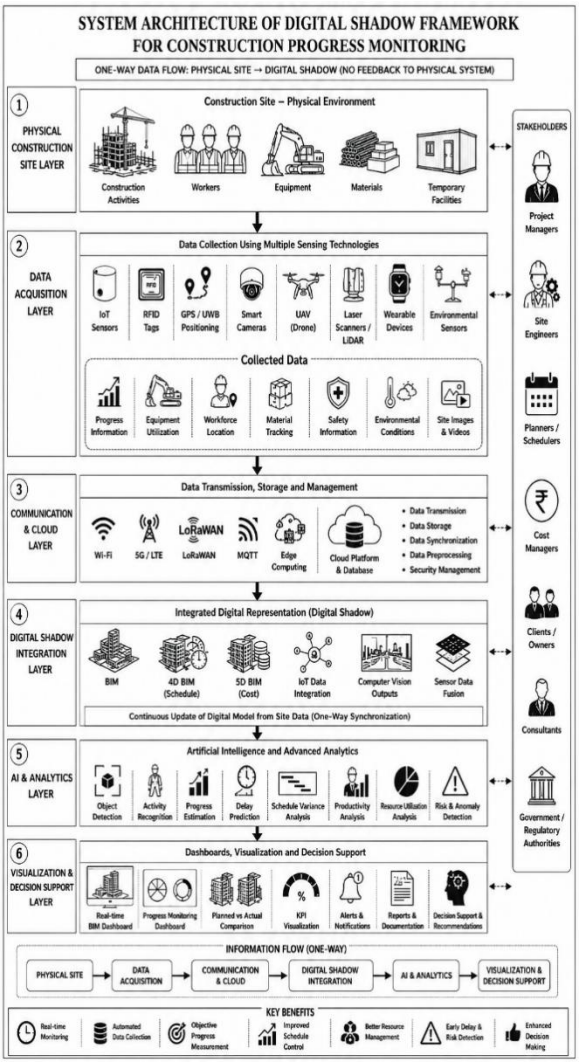


**Figure 2 System Architecture of Digital Shadow frame work for construction progress monitoring**

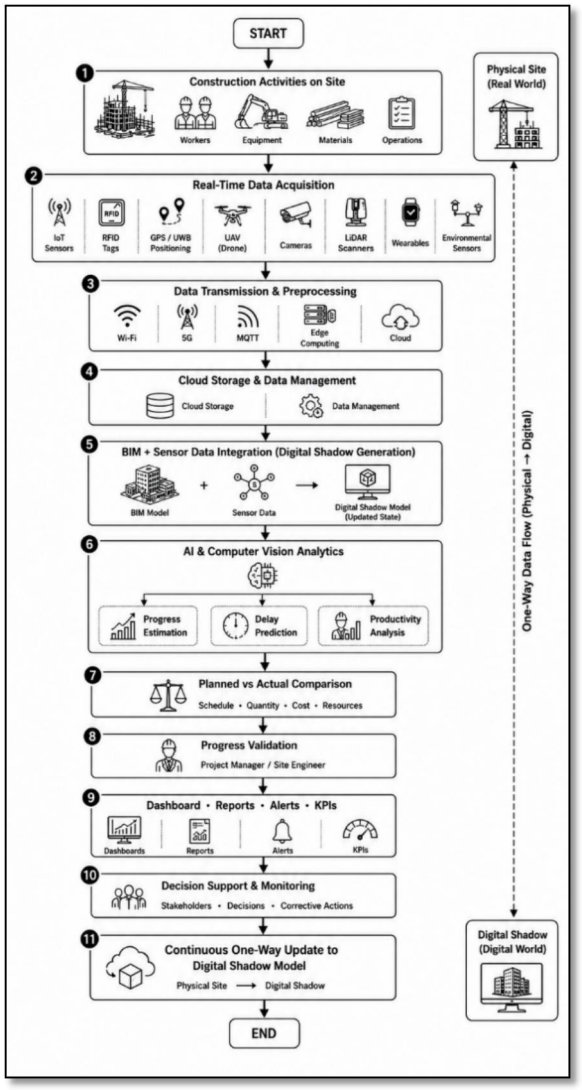


**Figure 3 Progress Monitoring Workflow**

**Analytics Layer:** The Delphi Round-1 evaluation of the Analytics Layer demonstrated exceptionally strong expert consensus across all five indicators (AN1–AN5). Every indicator satisfied the predefined consensus criteria, with median scores of 5, interquartile ranges of 0 or 1, and 100% agreement among the expert panel. AN5 achieved unanimous consensus, with all experts assigning the highest possible rating (Mean = 5.00; SD = 0.00), while AN1, AN2, and AN4 also exhibited very high agreement (Mean = 4.80; IQR = 0). Although AN3 displayed slightly greater variability, it maintained complete agreement and a high mean score (4.60). These findings (table 13) confirm that the proposed Analytics Layer effectively incorporates the essential analytical functions required for BIM-enabled Digital Shadow-based construction progress monitoring and is considered robust, comprehensive, and suitable for implementation within the overall framework.

**Table 1 Descriptive Statistics of Framework completeness layer**

| Item | Mean | Median | Mode | SD | IQR | Agreement (4 or 5) |
|---|---|---|---|---|---|---|
| FC1 | 4.20 | 4 | 4 | 0.61 | 1.00 | 90.0% |
| FC2 | 5.00 | 5 | 5 | 0.00 | 0.00 | 100.0% |
| FC3 | 4.80 | 5 | 5 | 0.41 | 0.00 | 100.0% |
| FC4 | 4.20 | 4 | 4 | 0.70 | 1.00 | 90.0% |
| FC5 | 4.10 | 4 | 4 | 0.61 | 0.75 | 90.0% |

**Table 2 Descriptive Statistics of Physical construction layer**

| Item | Mean | Median | Mode | SD | IQR | Agreement (4 or 5) |
|---|---|---|---|---|---|---|
| PL1 | 4.27 | 4 | 4 | 0.58 | 1 | 96.7% |
| PL2 | 4.90 | 5 | 5 | 0.31 | 0 | 100% |
| PL3 | 4.70 | 5 | 5 | 0.47 | 1 | 96.7% |
| PL4 | 4.63 | 5 | 5 | 0.49 | 1 | 100% |
| PL5 | 4.43 | 4 | 4 | 0.73 | 1 | 100% |

**Table 3 Descriptive Statistics of Data Acquisition Layer**

| Item | Mean | Median | Mode | SD | IQR | Agreement (4 or 5) |
|---|---|---|---|---|---|---|
| DA1 | 4.27 | 4 | 4 | 0.74 | 1 | 86.7% |
| DA2 | 4.60 | 5 | 5 | 0.50 | 1 | 100% |
| DA3 | 4.57 | 5 | 5 | 0.82 | 1 | 90.0% |
| DA4 | 4.60 | 5 | 5 | 0.50 | 1 | 100% |
| DA5 | 4.60 | 5 | 5 | 0.50 | 1 | 100% |

**Table 4 Descriptive Statistics of Digital Integration Layer**

| Item | Mean | Median | Mode | SD | IQR | Agreement (4 or 5) |
|---|---|---|---|---|---|---|
| DI1 | 3.83 | 4 | 4 | 0.65 | 1 | 83.3% |
| DI2 | 4.40 | 4 | 4 | 0.50 | 1 | 100% |
| DI3 | 4.27 | 4 | 4 | 0.69 | 1 | 90.0% |
| DI4 | 4.50 | 4.5 (≈5) | 5 | 0.51 | 1 | 100% |
| DI5 | 4.13 | 4 | 4 | 0.35 | 0 | 100% |

**Table 5 Descriptive Statistics of Analytics Layer**

| Item | Mean | Median | Mode | SD | IQR | Agreement (4 or 5) |
|---|---|---|---|---|---|---|
| AN1 | 4.80 | 5 | 5 | 0.41 | 0 | 100% |
| AN2 | 4.80 | 5 | 5 | 0.41 | 0 | 100% |
| AN3 | 4.60 | 5 | 4 & 5 (bimodal) | 0.50 | 1 | 100% |
| AN4 | 4.80 | 5 | 5 | 0.41 | 0 | 100% |
| AN5 | 5.00 | 5 | 5 | 0.00 | 0 | 100% |

**Table 6 Descriptive Statistics of Visualization Layer**

| Item | Mean | Median | Mode | SD | IQR | Agreement (4 or 5) |
|---|---|---|---|---|---|---|
| VS1 | 4.80 | 5 | 5 | 0.41 | 0 | 100% |
| VS2 | 4.80 | 5 | 5 | 0.41 | 0 | 100% |
| VS3 | 4.80 | 5 | 5 | 0.41 | 0 | 100% |
| VS4 | 4.80 | 5 | 5 | 0.41 | 0 | 100% |
| VS5 | 4.80 | 5 | 5 | 0.41 | 0 | 100% |

**Table 7 Descriptive Statistics of Decision Support Layer**

| Item | Mean | Median | Mode | SD | IQR | Agreement (4 or 5) |
|---|---|---|---|---|---|---|
| DS1 | 4.60 | 5 | 5 | 0.50 | 1 | 100% |
| DS2 | 4.80 | 5 | 5 | 0.41 | 0 | 100% |
| DS3 | 4.80 | 5 | 5 | 0.41 | 0 | 100% |
| DS4 | 4.60 | 5 | 5 | 0.81 | 0* | 86.7% |
| DS5 | 4.60 | 5 | 5 | 0.50 | 1 | 100% |

**Table 8 Descriptive Statistics of Practical Implementation**

| Item | Mean | Median | Mode | SD | IQR | Agreement (4 or 5) |
|---|---|---|---|---|---|---|
| PI1 | 4.87 | 5 | 5 | 0.35 | 0 | 100% |
| PI2 | 4.67 | 5 | 5 | 0.48 | 1 | 100% |
| PI3 | 4.47 | 5 | 5 | 0.78 | 1 | 86.7% |
| PI4 | 4.53 | 5 | 5 | 0.68 | 1 | 93.3% |
| PI5 | 4.60 | 5 | 5 | 0.68 | 1 | 90.0% |

Visualization Layer: The Delphi Round-1 evaluation of the Visualization Layer demonstrated exceptionally strong expert consensus across all five indicators (VS1–VS5). Each indicator achieved a median score of 5, an interquartile range of 0, and 100% agreement among the expert panel, thereby satisfying the predefined Delphi consensus criteria. The mean score for each visualization component was 4.80 (SD = 0.41), indicating consistently high expert endorsement of the proposed visualization mechanisms. The absence of ratings below 4 reflects unanimous agreement regarding the importance of integrating effective visualization capabilities for real-time construction progress monitoring within the BIM-enabled Digital Shadow framework. These findings (Table 14) confirm that the proposed Visualization Layer is comprehensive, robust, and suitable for implementation without requiring additional Delphi validation rounds.

**Table 9 Descriptive Statistics of Overall Evaluation**

| Section | Mean Range | Agreement Range | Consensus |
|---|---|---|---|
| Framework Completeness | 4.00–5.00 | 86.7–100% | ✓ Achieved |
| Physical Construction Layer | 4.27–4.90 | 96.7–100% | ✓ Achieved |
| Data Acquisition Layer | 4.27–4.60 | 86.7–100% | ✓ Achieved |
| Digital Integration Layer | 3.83–4.50 | 83.3–100% | ✓ Achieved |
| Analytics Layer | 4.60–5.00 | 100% | ✓ Achieved |

| | | | |
|---|---|---|---|
| Visualization Layer | 4.80 | 100% | ✓ Achieved |
| Decision Support Layer | 4.60–4.80 | 86.7–100% | ✓ Achieved |
| Framework Integration | 4.20–5.00 | 80.0–100% | ✓ Achieved |
| Practical Implementation | 4.47–4.87 | 86.7–100% | ✓ Achieved |

**Decision Support Layer:** The Delphi Round-1 assessment of the Decision Support Layer demonstrated strong expert consensus across all five evaluation indicators (DS1–DS5). All indicators satisfied the predefined consensus criteria, with median scores of 5, interquartile ranges between 0 and 1, and agreement levels ranging from 86.7% to 100%. DS2 and DS3 exhibited the highest level of agreement, each achieving a mean score of 4.80 with complete expert agreement and zero interquartile range. Although DS4 showed slightly greater response variability because a small proportion of experts assigned neutral ratings, it still achieved an agreement level well above the acceptance threshold. These findings (Table 15) validate that the proposed Decision Support Layer effectively integrates the essential capabilities required for intelligent construction progress assessment and management decision-making within the BIM-enabled Digital Shadow framework, thereby confirming its suitability for implementation without requiring further Delphi validation rounds.

**Practical Implementation:** The Delphi Round-1 analysis indicates strong expert consensus regarding the Practical Implementation of the proposed BIM-enabled Digital Shadow framework. All five implementation indicators satisfied the predefined consensus criteria, with median scores of 5, interquartile ranges of 0 or 1, and agreement levels ranging from 86.7% to 100%. PI1 received the highest level of support (Mean = 4.87), indicating that experts strongly believe the framework is practical and implementable in real-world construction projects. PI2 also achieved complete agreement with a high mean score of 4.67. Although PI3, PI4, and PI5 exhibited slightly greater variability because a few experts assigned ratings of 3, each indicator still exceeded the Delphi acceptance threshold and demonstrated strong overall agreement. The results (Table 16) confirm that experts consider the proposed framework to be both technically feasible and practically applicable for BIM-enabled Digital Shadow-based construction progress monitoring.

**Overall Evaluation:** The Delphi Round-1 evaluation demonstrates high to very high expert consensus across all nine sections of the proposed BIM-enabled Digital Shadow framework. Every assessment item satisfied the predefined consensus criteria (Median ≥ 4, IQR ≤ 1, and agreement ≥ 75%), with agreement levels ranging from 80.0% to 100%. Several items—including FC2, AN5, FI1, and all Visualization Layer indicators achieved unanimous or near-unanimous agreement. These findings (Table 17) provide strong empirical evidence supporting the completeness, technical validity, integration, and practical applicability of the proposed framework. Based on the achieved consensus, a second Delphi round is not required, and the framework can be considered validated for scholarly publication and subsequent implementation studies.

**Conclusions**

The Delphi Round-1 evaluation established a high level of expert consensus regarding the proposed BIM-enabled Digital Shadow (DS) framework for construction progress monitoring. Across all nine evaluation sections framework completeness, physical construction layer, data acquisition layer, digital integration layer, analytics layer, visualization layer, decision support layer, practical implementation, and overall evaluation all assessment indicators satisfied the predefined Delphi consensus criteria (Median ≥ 4, IQR ≤ 1, and Agreement ≥ 75%). Mean scores consistently exceeded 4.0, while agreement levels ranged from 80.0% to 100%, demonstrating strong expert endorsement of the framework's conceptual design, technical architecture, functional components, and implementation feasibility.

Several indicators achieved unanimous or near-unanimous consensus, particularly FC2, AN5, PI1, and all Visualization Layer indicators, reflecting exceptional agreement regarding the framework's completeness, analytical capabilities, visualization mechanisms, and practical applicability. The consistently low standard deviations and narrow interquartile ranges further indicate high stability and reliability of expert judgments across diverse domains of expertise, including BIM, construction management, artificial intelligence, computer vision, IoT, cloud computing, digital twins, and Construction 4.0.

Collectively, the findings provide robust empirical evidence that the proposed framework comprehensively integrates the essential technological and functional components required for BIM-enabled Digital Shadow–based construction progress monitoring. The validated framework effectively supports real-time data acquisition, digital integration, intelligent analytics, visualization, and decision support while demonstrating strong potential for practical implementation in construction projects.

Since all evaluation criteria exceeded the predefined consensus thresholds and no indicator required substantial revision, the Delphi panel reached sufficient consensus in the first round. Consequently, a second Delphi round was deemed unnecessary. The validated framework therefore provides a scientifically rigorous and practically applicable foundation for future prototype development, case-study implementation, and quantitative performance evaluation in real-world construction environments. All six objectives are successfully achieved through

literature synthesis, framework development, system design, and Delphi-based validation

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